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A Fusion Classification Prototypical for Eye State Recognition in Stroke Patients Using Electroencephalogram (EEG) Data

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Abstract: The electroencephalography (EEG) signal is a crucial part of Brain-Computer Interface (BCI) technology. Simply put, the BCI is a non-muscular channel for information transfer between the brain and other devices. The primary goal of BCIs is to restore some level of social interaction for those who are unable to use their mouths or hands because of neurological impairments. Classification of EEG signals is essential for many uses, including imaging of motor imagery, diagnosis of pharmacological effects, identification of emotions, prediction of seizures, detection of eye states, and many others. As a result, the construction of an autonomous solution in the medical arena necessitates a powerful classification model capable of efficiently processing the EEG information. Accurate diagnosis of an eye disease using EEG data is a challenging but essential task in medicine and daily life. The fundamental goal of this study is to develop a hybrid model based on machine learning that improves the accuracy with which the ocular status of stroke patients may be detected from EEG data. It can aid in finding and eliminating anomalies, and it can help in developing the robotic or smart machine-based answer to societal problems. To determine its usefulness and accuracy, this hybrid categorization model was compared to state-of-the-art machine learning methods. The experimental analysis proves that the suggested hybrid classification model outperforms the competition. The suggested hybrid model outperforms the state-of-the-art on every test and validation metric.

Keywords*: *BCI, EEG, CI, sleep-waking patterns.

1. Introduction

The Internet of Things is a promising emerging technology that is gaining popularity in many parts of the world. The immense strength and capability of the Internet of Things allows us to connect whenever, whenever, and through whatever network or service we choose. As the Internet of Things (IoT) develops into a formidable force for next-generation machinery, its influence on the existing business climate may become apparent. The Internet of Things is facilitating the creation of new solutions by companies and academics. They communicate with intelligent gadgets and things by utilizing the existing internet infrastructure to its full potential. It can also provide additional services and benefits to AI systems. In addition to machine-to-machine (M2M) interactions is at stake for the provision of exceptional services [2]. Hence, all IoT-based applications may soon have the option of automation [3]. The BCI only serves as a non-muscle communication channel between the brain and external equipment. The primary premise of BCI is to facilitate the contact of neurological sick individuals with others via brain signals. The categorization of EEG signals is a crucial prerequisite for many applications [4], including the classification of motor imagery, the diagnosis of pharmacological effects, the classification of emotions, the prediction and detection of seizures, the prediction and detection of ocular states, and many others. As a result, an effective classification model is required that can handle the EEG datasets more effectively and accurately, which will aid in the development of an involuntary resolution for the medicinal domain [5].

Before the advent of the IoT in healthcare or the Internet of Healthcare Things (IoHT), people relied on more traditional means of receiving medical care, such as calling their doctors, going to their offices, sending them texts, and so on. Because of the way that patient care was traditionally provided, it was not possible for medical professionals or hospitals to keep track of or monitor the health of a patient in real time [6]. There is a two-way

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exchange of information regarding the patient's health between the patient and the doctor. With their current state of health, the patient is able to make adjustments to their future goals and take the necessary precautions. IoHT has made the interactions between doctors and patients easier and more productive [7]. It has also led to considerable gains in the overall level of satisfaction and involvement of patients. A patient's use of a remote health monitoring system can shorten their time spent in the hospital and cut their out-of-pocket expenses for medical care. Moreover, it can improve the overall results of treatment and prevent patients from having to be readmitted to the hospital [8].

IoHT for patients encompasses of a diversity of wearable expedients that are available for purchase, such as fitness bands, smartwatches, and other gadgets that have the capability to communicate wirelessly. These cutting-edge devices are put to use for conducting individual surveillance. With the assistance of these ingenious devices, we are able to program reminders for a variety of different things, including our day-to-day calorie consumption, workout check-in days, variations in BP (blood pressure), schedules, and more [9]. When it comes to IoHT for doctors, the multiple wearable expedients and other home-founded observing expertise help the doctor maintain better track of the patient's health in a more efficient manner [10].

One of the difficult but crucial jobs, both in the medical field and in daily life, is the precise detection of the ocular condition using EEG data. The proper and precise cataloguing of the eye condition is helpful in an extensive assortment of applications, including the construction of human CIs for newborn babies, the identification of stress levels, and the detection of tiredness while driving. Several machine learning-based methods have occasionally been proposed for the classification of the EEG-based signal in a variety of applications. For the most part, they suggested conventional model classification models [11]. Nonetheless, there is still a need for an effective classification algorithm that can accurately and correctly categorize stroke patients' eye states based on electroencephalogram signals. This paper proposes a fusion-cataloguing model for electroencephalogram (EEG) signals-based eye state identification in stroke patients. The applicability and correctness of this fusion-cataloguing model have been examined in comparison to other conventional machine learning methods. With improved accuracy, this suggested classification approach builds a hybrid machine-learning model for classifying eye conditions in stroke patients using EEG signals [12].

2. Previous Related Work

Several researchers have studied the importance of IoHT, which can be helpful to make diagnoses and treatment of patients. A central health server connects a group of diverse health devices to form the IoHT network. It is possible to connect via cable or wirelessly. Smart health devices form the IoHT architecture [13] by working together to perform specified or specific tasks within the same application domain. The IoHT infrastructure may consist of a network of interconnected medical devices that all work together to accomplish their respective functions via a shared communication channel. These lines of communication make it possible to keep track of all sent and received information. The service providers can be reached via these channels of contact. What this means is that we may say that several companies are responsible for maintaining these channels of contact [14]. Security is essential to the IoHT network since the data it stores is part of an individual's eHealth records and contains private information about that person. Once the service provider has analysed the data from the various health devices, the information is given to the appropriate authorities or user. The typical IoHT structure consists of sensor-based devices, their associated actions, and the associated workflow. These smart gadgets rely on sensors and can talk to one another across wired or wireless networks [15].

The IoHT network is formed when a central health server links together a wide variety of health devices. It is possible to connect via cable or wirelessly. Smart health devices form the IoHT architecture by working together to perform predetermined prescribed responsibilities inside the same application domain. The IoHT infrastructure [16] may consist of many medical devices that work in tandem to accomplish their responsibilities via the communication channel. These lines of communication make it possible to keep track of all sent and received information. The service providers can be reached via these channels of contact. What this means is that we may say that several companies are responsible for maintaining these channels of contact. These intermediaries furnish the communication path with support and safeguards [17]. Security is essential to the IoHT network since the data it stores is part of an individual's eHealth records and contains private information about that person. [18].

While conducting analysis of mental healthcare, the EGG dataset is utilized more frequently. In this inquiry, machine learning strategies are utilized for the purpose of processing the statistical information that was gathered from the EEG dataset. The field of intelligent medical technology has made significant strides forward in the recent years. As a consequence of this, a range of clever machines have been observed to acquire real-time data from the scalp in a more efficient and accurate manner in comparison to traditional EEG equipment [19]. The muse band and the Emotiv EPOC headset are two instances of smart technologies that, according to an earlier study that was carried out by a group of researchers, are examples of portable technologies that are affordable, simple to use, and more accurate than conventional healthcare gear. Both the Emotiv EPOC headset and the muse band are capable of collecting data at a frequency of 128 hertz, but the Emotiv EPOC headset includes fourteen EEG sensors whereas the muse band only has four [20]. The EEG readings from the Emotiv EPOC headset are the main subject of this investigation. In the past, a team of researchers used EEG data from Emotiv EPOC headsets to categorize eye conditions [21]. They used a number of instance-based classification algorithms to predict the eye condition, and by employing the R-star algorithm, they were able to achieve an accuracy of 97.3%. Nevertheless, this prediction system was extremely slow, needing at least 2 hours to train on the data and 20 minutes to forecast the state of the eyes [22].

Another team of researchers used the same data set in conjunction with the incremental attribute learning model. The accuracy of this model was 76.6%. The authors used the standard deviation and channel average as novel characteristics for classifying ocular states [23]. Nevertheless, they had not addressed how long the model would take to process. A few more researchers classified the eye state using multilayer perception neural networks (NN) and k-nearest neighbours (kNN) models. The classification results showed that the kNN had prevailed since it had the best accuracy, 85.05% [24-25].

3. The Objective of the Proposed Work

1. The objective of this research is to improve a fusion prototypical based on machine learning to more accurately classify patients' eye states from EEG signals after a stroke.
2. To eliminate the difficulty of class imbalance by the elimination of outliers.
3. To provide a solution based on machine learning that can be used to create a robotic or smart machine that can improve people's quality of life in society.

4. The Proposed Work:

In this study, we present a hybrid classification model for EEG-based detection of the ocular status in ischemic stroke patients. In order to determine the efficacy and precision of this hybrid classification model, it has been compared to the standard machine learning methods. By combining traditional methods with machine learning, the proposed classification model may more accurately categorize stroke patients' eye states from EEG data. To further address the issue of class imbalance, it can also detect and eliminate anomalous data, providing a step toward developing a robotic or smart machine-based solution to improve people's quality of life.

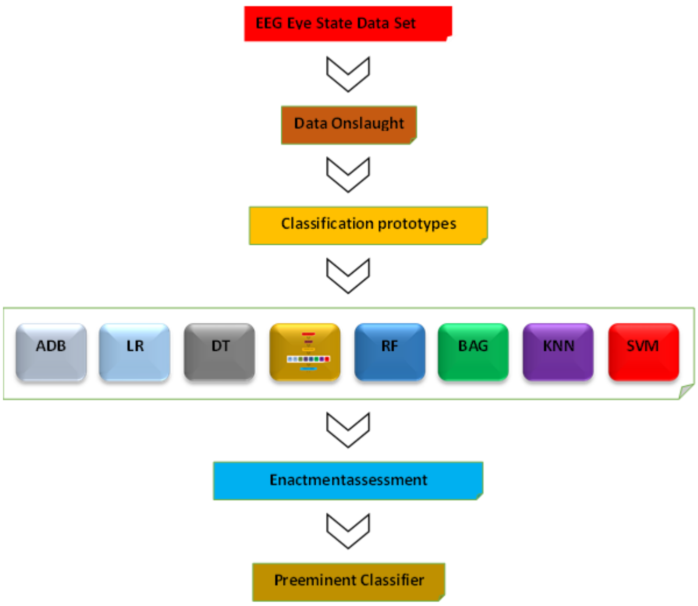

Fig I: Structure for the Classification Prototypical.

There are five fundamental stages to the categorization model evaluation framework.

- First, the EEG eye state dataset undergoes data pre-processing to remove any outliers or missing data.
- In the second stage, an EEG eye state dataset was analysed, and outliers were identified and removed using the isolation forest technique.
- This improved pre-processed data is then subjected to SMOTE (Synthetic Minority Oversampling Method) in order to discourse the class inequality problem.
- Fourth, the hyper tuned support vector machine model was fed data from this new balanced dataset

with 10-fold class validation approaches 70-30 ratio to assess the classification model's efficacy.

- The final phase involves analysing the results of the hybrid classification model in terms of its statistical parameters.

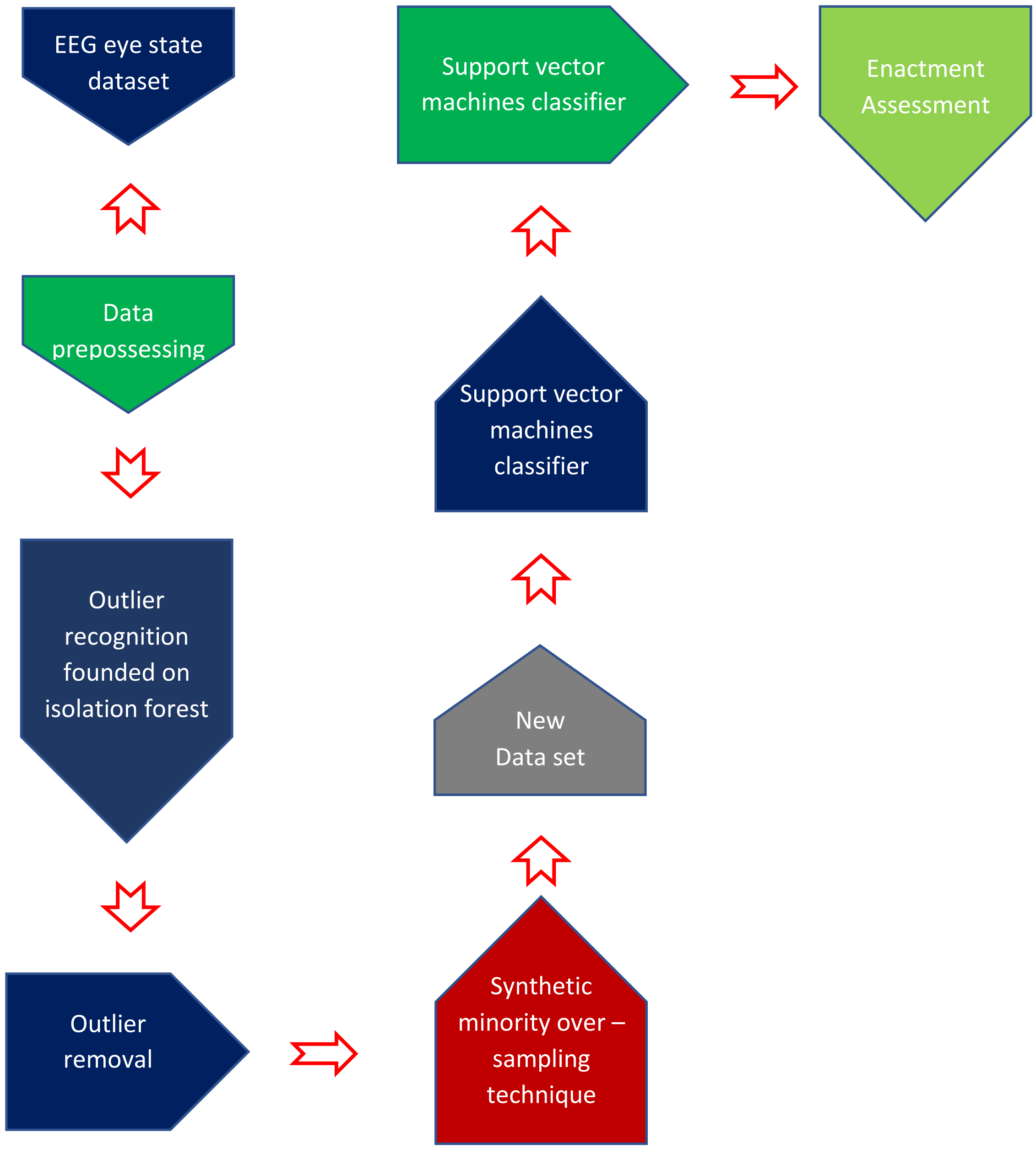

Fig II: The Proposed Algorithm flow chart.

1. The outlier is a critical component of any classification problem and has the potential to compromise the accuracy of the model. Thus, a reliable method capable of dealing with such circumstances is crucially needed. As an example of an unsupervised technique for outlier/anomaly detection problems, we have pre-processed the EEG-signal-based eye dataset using the Isolation forest algorithm. We have used this method to clean up our dataset of eye states based on EEG recordings.

4.2. One of the major problems that affects the effectiveness of classification models is class imbalance. Since a disproportionate share of the data comes from the minority group, it's possible that the results will be skewed in favour of that group. Hence, a reliable method that can deal with data imbalance is crucial. To this end, we employ the SMOTE (Synthetic Minority Oversampling Technique) algorithm, one of several unsupervised methods for addressing class imbalance, using an eye dataset based on EEG signals. Using this method, we were able to achieve class parity in our dataset of eye states measured via electroencephalography.

4.3. The support vector machine (SVM) is one of the most popular categorization techniques, finding use in nearly every industry. We have selected the SVM technique for the classification problem due to its robust history and wide application, and we have adjusted this algorithm to find the optimal parameters.

5. Result and Discussion:

Finding the right categorization model that fits well with the smart healthcare paradigms is a challenging but novel task. The primary objective of this learning is to improve an improved method for classifying stroke patients' eye states from EEG data using a hybrid model based on machine learning. Further, it can be used to construct the machinelike or insolent machine-founded resolution for societal welfare by addressing the problem of outlier recognition and elimination.

Using electroencephalogram (EEG) signals, these classification models have been utilized to detect the ocular condition in stroke patients. The prototypes have been calculated using a 10-fold class validation policy with a 70-30 split between training and testing data. Nonetheless, arithmetical analysis has been carried out to compute classification model performance. The purpose of this investigation is to assess the suitability and accuracy of the suggested hybrid model in comparison to the more predictable machine learning methods.

In order to conduct an analysis of the classification findings, we have relied on the following statistical parameters: accuracy, precision, recall, and f1-score. We were able to determine the precision of classification models as well as their applicability with the assistance of these performance evaluators. The accuracy, appropriateness, and performance of categorization models have been measured with the help of these performance assessors.

5.1. Accuracy:

It is a typical metric for classifying test results numerically. Increased precision indicates a more efficient system.

$$\text{Accuracy} = \frac{TN+TP}{Total\ data\ Sample}\ X100$$
(1)

5.2. Recall:

Specificity was defined as the absence of incorrect data classification. True Negative Rate is another name for it (TNR). Figure IV displays the recall of the current method in comparison to commonly utilized methods.

$$\text{Specificity} = \frac{TN}{TN+FP}\ X100 \quad (2)$$

5.3. Precision:

The present work is believed to have the precision to provide useful outcomes. The value of precision indicates what fraction of valid affirmative identifications were made. Figure III displays the results of a comparison between the current model and the commonly used techniques in terms of accuracy. The present system's accuracy was determined by

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

5.4. Sensitivity:

The accuracy with which the model places the test data into one of its classes constitutes the present method's sensitivity. How many true positives were successfully detected was the question it addressed. True Positive Rate is another name for it.

$$Senstivity = \frac{TP}{TP+FN}\ X100 \quad (4)$$

Table 1: Enactment Assessment of the Classification Process on Eye State Data.

Classification Model	**5-Fold**				**10-Fold**			
	Precision	**Recall**	**F-Score**	**Accuracy**	**Precision**	**Recall**	**F-Score**	**Accuracy**
SVM	0.88	0.89	0.88	88.42	0.89	0.89	0.89	89.28
KNN	0.95	0.95	0.94	94.71	0.94	0.94	0.94	94.26
RF	0.91	0.92	0.90	91.94	0.92	0.91	0.91	91.36
BAG	0.89	0.89	0.88	89.26	0.89	0.89	0.89	89.15
ET	0.95	0.95	0.94	93.27	0.93	0.93	0.93	93.24
DT	0.86	0.85	0.84	84.38	0.85	0.85	0.86	85.8
LR	0.68	0.65	0.64	64.57	0.66	0.65	0.64	65.4
ADB	0.76	0.75	0.75	74.14	0.74	0.75	0.74	73.1

PHM	0.99	0.99	0.99	98.12	0.99	0.98	0.98	98.8

Table I shows the outcome of nine classification models for identifying the eye (stroke patients) state by using the EEG data, grounded on the four different enactment assessors. The fundamental motivation behind this experiment is to find a way to improve the precision with which robotic or smart machine-based solutions may be implemented to improve people's quality of life and the world at large. In order to determine the efficacy and precision of this hybrid classification model, it has been compared to the standard machine learning methods. The experimental evaluation demonstrates that the suggested hybrid classification model outperforms competing classification models in terms of accuracy. When tested using a variety of validation criteria, the suggested hybrid model consistently produces the best results (cross-validation policy 5-fold, and 10-fold).

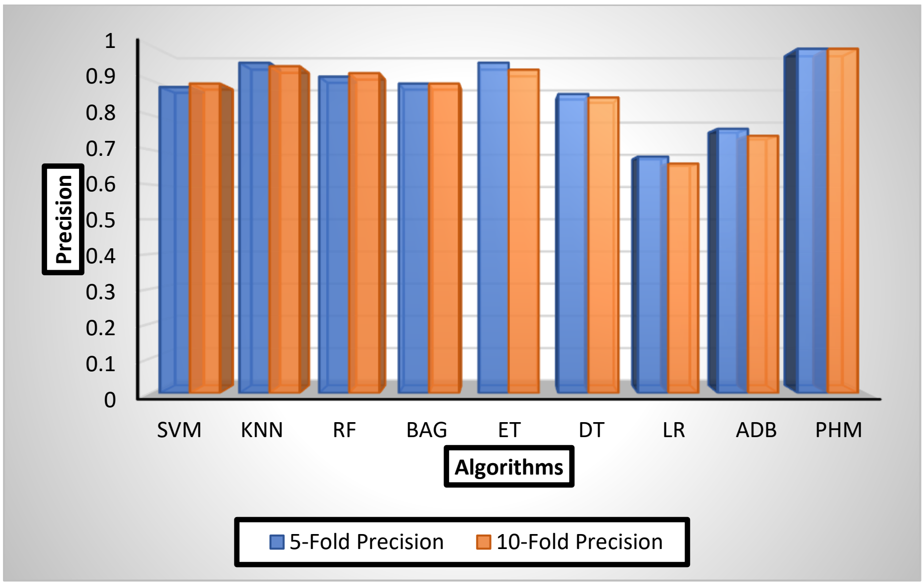

Fig III: Precision Comparison of 5 and 10 fold classification algorithm.

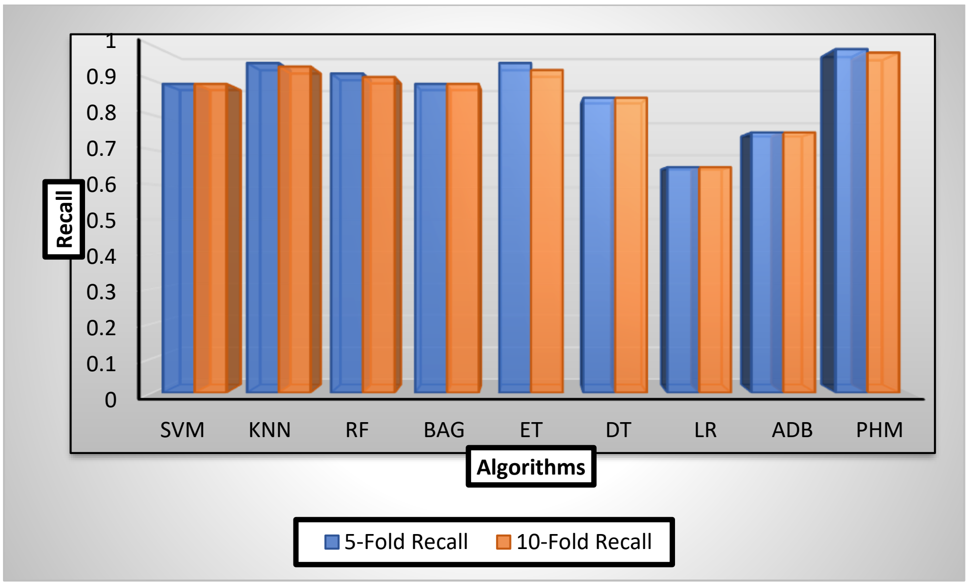

Fig IV: Recall Comparison of 5 and 10 fold classification algorithm.

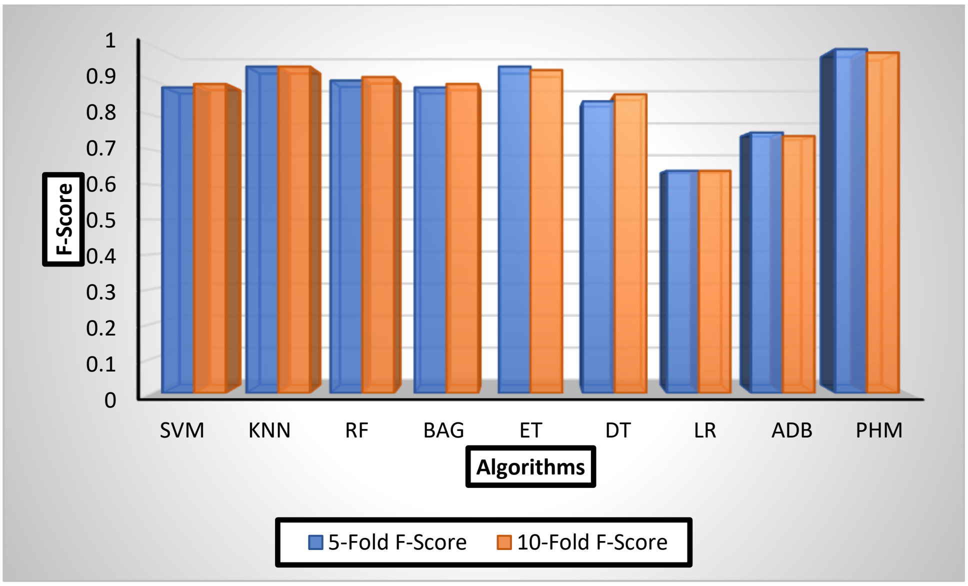

Fig V: F-Score Comparison of 5 and 10 fold classification algorithm.

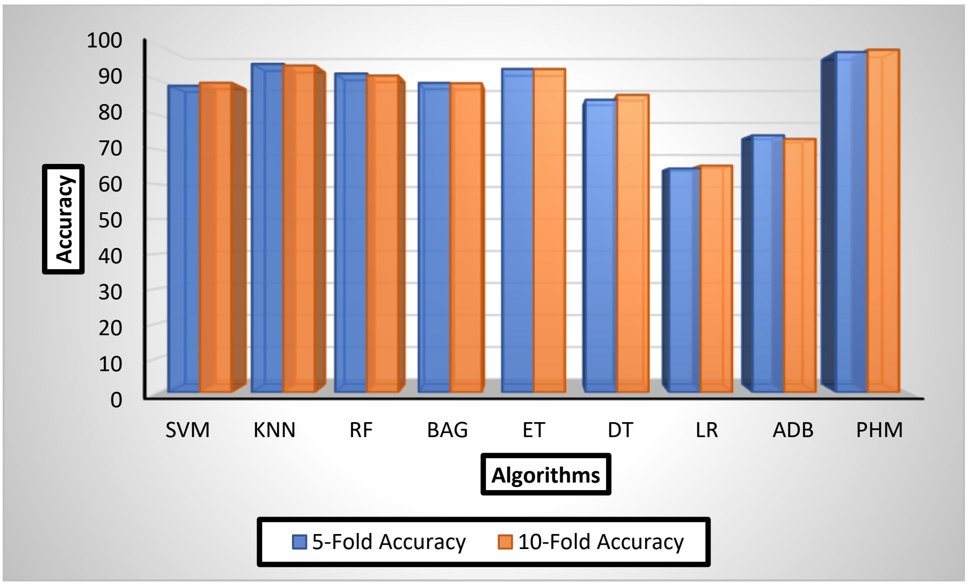

Fig VI: Accuracy Comparison of 5 and 10 fold classification algorithm.

In Figures III, IV, V, and VI, the x-axis displays the various categorization models employed while the y-axis displays their relative Precision, F-Score, Recall, and Accuracy. The model evaluation shows that compared to previous classification models, our suggested hybrid classification model performs extraordinarily well and with higher accuracy. The experimental evaluation shows that compared to existing classification models, the suggested hybrid classification model works extraordinarily well and with higher accuracy. The recommended hybrid model has the highest accuracy across all validation measures.

Conclusion and Future Scope:

Finding the right categorization model that fits well with the smart healthcare paradigms is a challenging but innovative mission. In the healthcare sector, even a little verdict can go a long way toward constructing the mechanical or machine-based resolution that will aid people and address the system's many flaws. Classification of electroencephalogram signals is crucial for many uses. To aid in the creation of an autonomous solution for the medical domain, it is necessary to have a classification model that is capable of handling EEG datasets with greater adequacy and classification accuracy. The fundamental goal of this study is to develop a hybrid model based on machine learning to improve the accuracy with which eye status can be classified from EEG signals in stroke patients. In addition to being able to assist in the development of the robotic or intelligent machine-based solution for societal well-being, it is also capable of handling the problem of outlier detection and eradication. Comparisons have been made between this hybrid classification model and the traditional approaches utilized in machine learning in order to ascertain the efficacy and accuracy of the former. The empirical evaluation reveals that the proposed hybrid classification model achieves a higher level of accuracy than other classification models that are currently available. The hybrid model that is recommended always performs better than its rivals do across a wide variety of tests and validation metrics. The algorithmic and data-driven perspectives will be added to this empirical investigation in the future.

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